An Emergent Economics of Ecosystem Management

Paper Presented at the New Zealand Agricultural and Resource Economics Society
Conference 24-25 August 2006

By **Edward J. S. Hearnshaw**[1], **R. Cullen**[2] and **K. F. D. Hughey**[3]
[1]Student, Commerce Division, Lincoln University
[2]Professor of Resource Economics, Commerce Division, Lincoln University
[3]Professor of Environmental Management, ESD Division, Lincoln University

---

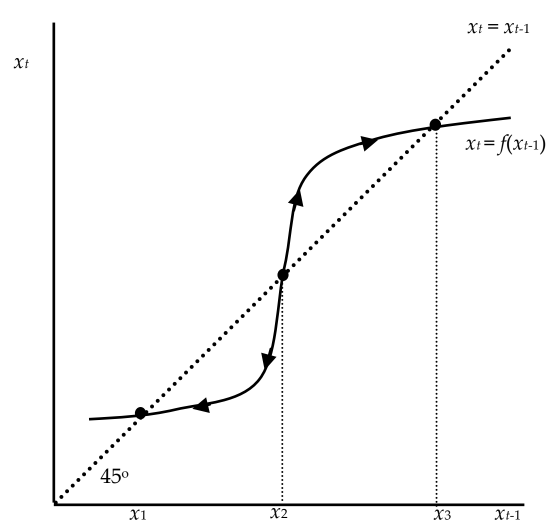
Abstract: Economics is an evolving and emerging filed of study, so is the management of ecosystems. As such, this paper delineates the co-evolution of economic evaluation that reflects the various recognized ecosystem management approaches of anticipative, adaptive and capacitive ecosystem management. Each management approach is critiqued and from this theoretical analysis an emergent approach for the management of ecosystem is put forward, which accordingly suggests an alternative methodological approach for economic evaluations.

Keywords: Complexity, creativity, economic evaluation, ecosystem management, evolution, open systems, rationality.

1.0 Introduction

We begin our understanding of ecosystems with a critical ecological insight; the development of ecosystems cannot be appropriately modeled in a linear manner, as depicted by overly mechanistic ‘succession-to-climax’ ecological models in which a global equilibrium prevails. Rather, we must utilize non-linear models for our understanding of the development of ecosystems, whereby multiple equilibria exist signifying that systems are not globally stable, but only locally so (see Figure 1).

Figure 1: A simple graphical representation in discrete time of a dynamic non-linear model. The system is shown to have multiple equilibria demarked by x_1, x_2 and x_3.



Importantly, this phenomenon of multiple equilibria is not simply a mathematical artifact as might be insinuated from Figure 1, as there exists an ever-growing array of empirical evidence depicting naturally occurring multiple equilibria (*i.e*. multiple system states) and transitions among them (*e.g*. Walker *et al*., 1981; Estes & Duggins, 1995; Perrings & Walker, 1995; Walker *et al*., 1997; Nyström *et al*., 2000; Carpenter, 2001; Gunderson, 2001; Scheffer *et al*., 2001; Walters & Kitchell, 2001; Danell *et al*., 2002; Peterson, 2002; Post *et al*., 2002).

Now, given that multiple system states exist that are only ever locally stable, it immediately begs the question, as to which system state should actually be selected and managed for by the resource manager. Presumably, ecologists would contend that this problem is 'elementary' in that the most appropriate system state to select and manage for is that which is ecologically 'superior' to alternative systems states, by way of its keystone species, or its ecological stability, biodiversity, or maybe its ecological ascendancy (see Nielsen & Ulanowicz, 2000). However, previously, we have concluded that it is not possible to determine which system state is in fact ecologically superior (Hearnshaw *et al*., 2005). That is, categorical statements about a system state for a particular ecosystem cannot be determined by a value-free desire for a strictly ecological and 'objective' demarcation of the appropriate system state (Regier, 1993; Kay & Regier, 2000). As such, if scientific demarcations are not useful, then it would seem that the most suitable means of determining the appropriate system state for management is via economic evaluation. Selection of the managed system state, then, would be deciphered by its generation of utility, determined by the multi-attribute bundle of ecosystem goods and services that the system state supplies to society. Needless to say, economic systems are intimately linked with ecosystems, as society depends on its goods and services for its well-being and prosperity.

But, of course, what remains is determining the most suitable approach for ecosystem management in deciphering the most desirable system state. In deciphering this ecosystem management approach, the reader is pre-empted for what might seem an undue deliberation of the very methodological foundations of economic evaluation itself. But, these issues found in these economic depths are of profound importance for the management of ecosystems, as ecosystems that resource managers administer provide the 'economic-ecologic link' to form what ecosystem management is genuinely founded upon.

2.0 Anticipative Ecosystem Management

The underlying premise of the one-time orthodox approach to the management of ecosystems, 'anticipative ecosystem management' (henceforth termed by acronym as *ANEM*), is that the resource manager, can anticipate or predict *a priori* the future system states of the ecosystem (Meffe *et al*., 1996). Accordingly, with the ability to predict the future, *ANEM* is said to be able to decipher by means of evaluation the most desirable system state, that which maximizes utility.

Significantly, readers of economic literature would recognize that the predictive nature of *ANEM* is well modeled in economic expressions by neoclassical economic theory, because like *ANEM*, neoclassical economics holds close the 'Laplacean aspiration' that the future can be predicted 'categorically'. With such definitive convictions of predictive power, *ex ante* economic evaluations by neoclassical economics, and therefore *ANEM*, is said to deduce the optimal system state by equilibrium analysis, a method whereby the optimum where utility is maximized is determined with the 'analytical equilibrium construct'.

In its static form, analytical equilibrium is simply the determination of outcomes from 'timeless' interactions of economic forces, whereby equilibrium acts as an ever-motionless 'stationary state'. Early theoretical economic work in deciphering the optimal management of ecosystems in such a manner was performed through static equilibrium analysis, most famously portrayed by Gordon (1954) on problems of 'renewable resource harvesting'. However, with the advancement of economic theory, accounting for temporality and dynamism in the economic analysis of ecosystem management has since been analysed by Hamiltonian analysis and logical time, which effectively sees time as an 'analytical clock', so that solutions are run instantaneously through until optimality is established as if time were reversible (see Clark, 1973; 1990; Dasgupta & Heal, 1979; Krautkramer, 1985). Significantly, with dynamic analysis, equilibrium is identified by the 'steady state', so that configurations can be viewed as converging directly towards the equilibrium construct.

For economic evaluations, however, economic analysis by logical time cannot be utilized. Instead, economic evaluations are made in the present under time conditions known as 'historical time', where time just goes on and on and never back. It is economic common sense, that the optimal rule of evaluation by equilibrium analysis is expected utility theory. Briefly, expected utility theory states that the resource manager 'chooses' between 'uncertain' system states by evaluating their expected utilities, that is, their weighted sums obtained by adding the utility values of system states multiplied by their associated probabilities. Hence, the resource manager is assumed to have: one, a complete record of the exhaustive set of system states; two, the understanding to compute uncertainty as 'risk' by way of knowing state probabilities *a priori*; and three, the correct and identical beliefs about the utilities of each system state (Machina, 1987; Katzner, 1998).

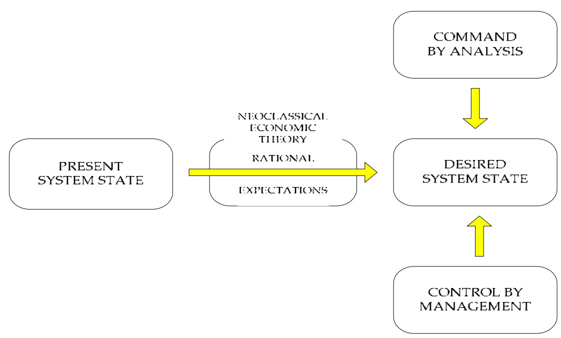
Of significance, the underlying epistemology of equilibrium analysis is 'Cartesian rationalism', which is a necessary position if the resource manager is to determine probabilities *a priori*, so that the optimal system state can be deciphered from deduction alone by various unwavering axioms of rational economic behaviour. Hence, from these very axioms the resource manager is said to be globally rational, endowed with boundless cognitive computational capabilities. Despite, global rationality the resource manager is not assumed to maintain 'self-fulfilling expectations', even probabilistically, but rather 'rational expectations'.

Specifically, the hypothesis of rational expectations contends that the expectations of the resource manager will be distributed about the prediction of the actual objective probability distribution of system states at any moment in time (Muth, 1961; Lucas & Prescott, 1971). Thus, the expected forecast error of the resource manager is assumed to be zero. Importantly, correct expectations is the single unifying criterion essential with neoclassical economics, as this "appears to be an essential property of [an analytical] equilibrium" (Phelps, 1987; *p*. 177). As such, surprises defined as differences between that rationally expected and the actual outcomes are alleged to be the sole result of stochastic disturbance events that are exogenous to the ecosystem, which can be captured in the variance of the stochastic term ε, often represented as the 'error term' in the simple equation $y = \alpha + \beta x + \varepsilon$. Hence, for economic evaluations to account for these disturbances, must conjoin expected utility theory with a mean stochastic error function.

2.1 Command-and-Control

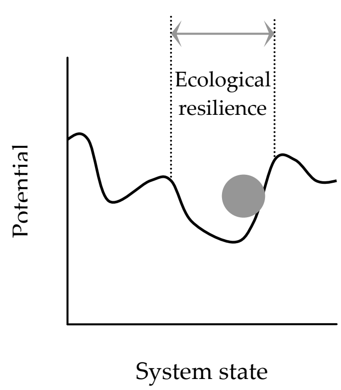
Economic evaluations, it is said involves an explicit distinction between the 'epistemological uncertainties' of the resource manager, which are absent, and disturbance events. Therefore, it is presupposed that resource managers have sufficient information to understand the model ecosystem. Hence, the managerial implications of *ANEM* can be limited to first, commanding the system to the desired system state, and secondly, controlling the disturbance function ε, so that the desired system states is managed into perpetuity (see Figure 2).

Figure 2: The 'command-and-control' strategy.



One means for accounting for control of the desired system state is to presume that the system state probabilities represent each state's ecological resilience ($R_j \cong p_j$), a measure of the magnitude of disturbance the system state can absorb without transitioning to an alternative system state (Holling, 1973; 1986; Holling *et al*., 1995) (see Figure 3).

Figure 3: 'Stability profile' depicting ecological resilience. The width of the system state 'cup' dictates the magnitude of the state's resilience.



It is possible at this point to represent this simple 'command-and-control' problem formulaically. Indeed, let us assume that the ecological resilience R_j of the present system state j, requires a managerial shock ε_m commanded from equilibrium analysis to make a state transition to the desired system state k. Thus, the magnitude of ε_m needs to be greater than R_j. Once the transition is complete the system is controlled so that if a stochastic disturbance ε is greater than R_k, then further managerial input ε_m is made to make the transition back into the desired system state k, so as to allow the continuation of the system state k and hence, the maintenance of utility maximisation.

2.2 Information and Bounded Rationality

Despite its elegance the rational expectations hypothesis has come under much criticism. Specific criticism concerns that if the disturbance function ε was zero, then rational expectations would be no different to self-fulfilling expectations. Certainly, Poole (1976; *p*. 504) came to this assessment, when he surmised that:

> "…rational expectations theory might be regarded … as only slightly amending [defunct] perfect certainty models. One needs only to substitute the assumption of perfect knowledge of probability distributions for the assumption of perfect knowledge of outcomes".

Nevertheless, rational expectations need not be criticized for its untenable claims as to the 'knowability of the future' only. As to assume that the epistemology of the resource manager to be free of systematic error, requires that the manager is, one, instantaneously endowed with a sufficient level of information prior to any acknowledged learning, which two, can be absorbed in its entirety. Moreover, rational expectations also makes the unsound assertion that information collection, deliberation, and managerial transitions ε_m between system states are not only timeless, but 'costless', so that the manager need not account for the magnitude of the gain in expected utility. Any gain, no matter how infinitesimal is considered worth having.

Not surprisingly, the extremeness of the assumptions of rational expectations have not been vindicated empirically, as there is a large body of evidence that indicates that rational expectations and the axioms of global rationality are in direct disagreement to how actual economic agents actually behave when left to their own economic devices (Allais, 1953; Abbot, 1955; Lichtenstein & Slovic, 1971; 1973; Tversky & Kahneman, 1971; Kahneman & Tversky, 1973; 1979; 1982; Kahneman *et al*., 1982; 1990; Machina, 1982; 1987; Smith *et al*., 1988; Thaler, 1992; 1994; Ramon *et al*., 1993; Hey, 1994; Bateman *et al*., 1997; Gintis, 2000). From this of empirical evidence, Starmer (1999; *p*. F8) concludes that:

> "One thing we have learned … is that [expected utility theory] is descriptively false. Mountains of experimental evidence reveal systematic violations of the axioms of [expected utility theory], and the more we look, the more we find".

The numerous empirical violations of expected utility theory have led to the emergence of several 'modified theories of expected utility', such as Loomes and Sugden's (1982) 'regret theory', and 'prospect theory' developed by Kahneman and Tversky (1979). However, while these modifications are improvements, these attempts have not gone far enough. For while these modified theories appear to be consistent with empirical behaviour, this is only when the resource manager is already given the necessary information on the probabilities with which to choose the appropriate system state in the economic evaluation. In fact, it is this very problem of 'information' that seems to be an underlying problem with equilibrium analysis. After all, for the axioms of global rationality to hold true the resource manager must be able to know and process all relevant information.

It seems that unlike theories developed in the natural sciences, where the underlying assumptions are developed from empirical evidence of the phenomena, the underlying assumptions of equilibrium analysis is founded on what seems to be contradicted by empirical evidence. Indeed, deductive economic analysis with a rationalist epistemology sets such a large requirement for notions of perfect information and knowledge that it is an impossible requirement for any realistic notion of what could be expected of the resource manager.

What is more, when rationality is axiomatized, choice is illusory and reduced to an instantaneous operation of deduction. The main limitation is that deductive inferences do not allow the resource manager the real ability to learn because all logical arguments depend on given axioms. As Loasby (1976; *p*. 5) recognized: "if knowledge is perfect, and the logic of choice complete and compelling, then choice disappears; nothing is left but stimulus and response". Nevertheless, if choice is to be considered 'real' in an economic evaluation, then knowledge must not be complete (Lawson, 1997; Loasby, 1999). Quite simply, the failure of equilibrium analysis is that it has not engendered a plausible account of economic agency (Georgescu-Roegen, 1971).

Of course, these failures of global rationality were first fully expressed by Simon (1955; 1959) who in doing so exposed the 'cognitive dimension' of the economic agent, and by implication the unrealistic notion of utility maximization. There is a reason as to why global rationality breaks down for economic evaluations involving ecosystems, as beyond a certain level of information the computational capacity of economic agents ceases to cope. In the presence of this so-called 'computational complexity', it is extremely difficult to calculate optimal solutions (see Leijonhufvud, 1993). Indeed, Simon (1988; *p*. 71) further stipulates that:

> "A theory of rationality that does not give an account of problem solving in the face of complexity is sadly incomplete. It is worse than incomplete; it can be seriously misleading by providing 'solutions' to economic questions that are without operational significance".

We can surmise that equilibrium analysis might be able to generate optimal solutions where the problem evaluated is so profoundly simple, that the information requirements and deliberation time in the economic evaluation are truly minimal (Dasgupta & Heal, 1974; Dasgupta, 1982; Clark, 1990). Needless to say, but these simplistic problems are not observed with ecosystems, which require a significant abundance of information in their modeling, so that if *ANEM* were implemented for ecosystem management the potential for gross systematic error is significant.

Indeed, in requiring simplicity in the ecosystem investigated so as to command-and-control these systems, resource managers have sought to simplify them by stabilizing ecosystem outputs, reducing system state alternatives, minimizing disturbance events and sustaining utility patterns (Ludwig *et al*., 1993; Holling & Meffe, 1996; Carpenter &

Gunderson, 2001). These attempts to simplify ecosystems have inevitably led to compromising the capacity of ecosystems to buffer disturbances because of the reduction in diversity within the system, ultimately leading to ecological catastrophe (Meffe *et al*., 1996). Holling and Meffe (1996; *p*. 329) conclude that:

> "The command-and-control approach, when extended uncritically to the treatment of [ecosystems], often results in unforeseen and undesirable consequences. A frequent, perhaps universal result of command-and-control… is reduction of the range of natural variation of systems [*i.e*. biodiversity] – their structure, function, or both – in an attempt to increase their predictability" (Holling & Meffe, 1996; *p*. 329).

Despite these difficulties, we have an alternative to global rationality in the form of 'bounded rationality', which is not to be confused with irrationality (March, 1994), but rather contends that economic behaviour is "intendedly rational but only limitedly so" (Simon, 1961; *p*. xxiv). Specifically, bounded rationality explicitly recognizes the cognitive constraints on the resource manager during the process of economic evaluation. These constraints on the capabilities of the manager are according to Simon (1955; 1959), the result of inadequately being able to process sufficient information, which thus places bounds on the resource manager's capabilities to know the extent of their alternatives.

2.3 Learning and Heuristics

In light of our present limits to our epistemological understanding of nature, we must improve the basis of our knowledge and information of ecosystems by focusing on learning. Learning arises from immediate experience, which requires a different mode of inference from that of deduction. After all, why should one be required to learn if one is already assumed to have perfect knowledge? Seeing as learning must begin from where we are in a descriptive sense, our learning processes is best exemplified through the logic of induction developed by the epistemology of 'Cartesian empiricism', the other side of the Cartesian coin. Thus, with inductive inferences, we infer in the opposite manner to deduction, that is, we infer from particular experiences and move towards more general claims.

Nonetheless, with equilibrium analysis seemingly rejected because of our bound rationality, where does one begin with induction? After all, with the application of deductive inference, which requires the fixity of its axioms, neoclassical economists have neglected the means that gave rise to optimal rules of evaluation, such as expected utility theory (Foster, 2004). That is, resource managers are not just to 'choose' the system state, but must also 'choose how to choose'. So, learning and bounded rationality are not simply about information, but rather first and foremost it is about the determination of a means for processing and analysing information, which is indecently what knowledge actually is. However, with equilibrium analysis, knowledge is considered perfect and is assumed to be of the same nature as information. But, when bounded rationality is properly acknowledged, knowledge and information become quite distinct projects.

For these reasons, at least at the initial stages of learning, one must begin by simply choosing a system state by trial-and-error. However, over time, as learning persists it is assumed that more utilizable general statements about the means of choosing can be deciphered (Staddon & Simmelhag, 1971; Einhorn, 1982). These generalizations develop in the form of heuristics, that is, 'fast and frugal evaluation rules', which are held on too, until new knowledge is obtained and better heuristics are devised in this evolutionary process of learning (Arthur, 1994). However, it is noteworthy that there must be heuristics behind heuristics, so to speak, as while inductive inference brings together many observations from which a generalized pattern can be made, it is first required that the economic agent in order to obtain the pattern, must be able to recognize that a pattern exists. Thus, data never induces generalizations, only the economic agent does, whether cognizant or not.

Of further importance, the evaluation mechanisms to which heuristics for economic evaluation hold are not governed by methods of optimization, but seem to be by Simon's (1955) 'satisficing hypothesis', whereby evaluations are performed by momentary and presumably rudimentary information searches, rather than through an expansive and fully cognizant analysis (Tversky & Kahneman, 1974; Gigerenzer *et al*., 1999; Gigerenzer & Selten, 2001). Moreover, given that heuristics evolve inductively from particularities, it suggests that heuristics while knowledge-increasing are extremely context dependent and thus, unlikely to provide a lot of generalizability for evaluating an array of ecosystems (Lichtenstein & Slovic, 1971; Tversky & Kahneman, 1980). Consequently, heuristics would seem like an unwise methodology for ecosystem management, because their inherently low cognitive control and low processing awareness would result in ongoing biases resulting in the maintenance of systematic error (Kahneman *et al*., 1982; Hammond *et al*., 1987; Kahneman, 2000).

Significantly and somewhat surprisingly, both critics and advocates of global rationality and optimal rules of evaluation whereby trajectories lead unwaveringly towards equilibrium, agree on the empirical evidence observed and the subsequent descriptive utilization of heuristics. But, whereas critics see this as overwhelming evidence that utility maximization and equilibrium analysis is flawed, advocates of equilibrium analysis interpret these findings quite differently. As a matter of fact, advocates believe that this empirical evidence is the most convincing rationalization for utilizing equilibrium analysis, as where such analysis is not used the resource manager will evaluate poorly by way of heuristics. Therefore, equilibrium analysis allows the resource manager to evaluate in a globally rational manner, rather than wallow simply in descriptive empiricism (Dyer *et al*., 1990). Hence, with knowledge of both modeling by optimal rules of evaluation available (which needless to say, are also inductively inferred in the sense of inducing the deciphering the best mathematical models, so as to be used in a deductive fashion), it thus seems appropriate to utilize these methods of economic evaluation so as to progress towards optimality (Baron, 2000). In doing so, we relieve ourselves of the problems of knowledge and can focus on the problems of information alone.

Methods that potentially lead to improvement in economic evaluation from descriptive evaluation rules to normative optimal rules of evaluation are called prescriptive methods. Hence, while normative evaluations tell us how the resource manager ought to behave and descriptive evaluations tell us how the resource manager actually behaves; it is prescriptive evaluations which tell us how the resource manager can significantly improve their process of economic evaluation. Thus, despite the presence of gross violations of expected utility theory and the fact that economic agents do not actually think in the terms of probabilities, this does not invalidate the methodology of its prescriptive possibilities, but only of its descriptive potential (Kahneman & Tversky, 1972; 1978; Manski, 2004). Indeed, Friedman (1953) once argued that assumptions of global rationality should not be taken literally, because economic agents should behave 'as-if' they were globally rational, so as to make better economic evaluations. Thus, we should not reject the use of expected utility theory as long as we recognize that economic agents do not actually follow these axioms of rational economic behaviour, but can merely act as-if they have in a prescriptive sense.

3.0 Adaptive Ecosystem Management

Whilst learning to some degree will almost always occur, it is the proposition of a method that is truly cognizant, prescriptive and analytical to its process of learning that is often considered the 'panacea' to problems of ecosystem management. It is this differentiable process of learning then that brings into being a meaningfully different approach to ecosystem management, coined 'adaptive ecosystem management' (*ADEM*) (Holling, 1978; Walters, 1986).

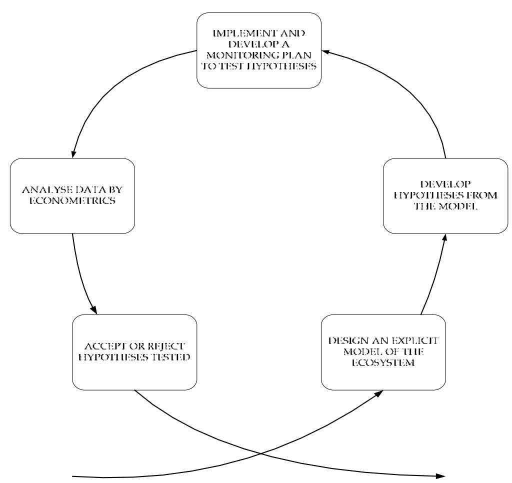
Naturally, *ADEM* accepts uncertainty generated from bounded rationality, and thus treats management failure and surprises as 'opportunities for learning' through a need for further discovery (Dempster, 1997; Stankey & Shindler, 1997). This is of course in stark contrast to *ANEM*, which focuses solely on procedures of efficient allocation and envisages any deviations from that expected as random anomalies from disturbance events. Hence, rather than using existing information, which is assumed wishfully to be perfect and complete, so as to predict the optimum system state, *ADEM* explicitly recognizes the existence of systematic error and constraints on information explicitly, which while a source of economic inefficiency, can it is believed be resolved through this process of analytical learning (Holling, 1978; Walters, 1986). Thus, "in theory, [*ADEM*] recapitulates the promise that Francis Bacon articulated four centuries ago: to control nature one must understand her" (Lee, 1999; *p*. 9).

Accordingly, to learn in an analytical manner, and in turn reduce uncertainty and develop theories, we must engage in scientific experimentation by describing information in meticulous detail, which over time it is hoped can generate model representations (Lee, 1993; Berkes & Folkes, 1998; Walker *et al*., 2002; Norton, 2005). Indeed, models are important where bounded rationality is prevalent, because "the usual experience with ecosystem data is that there is not enough to define the biology with any confidence, but far too much for a single human mind to assimilate" (Lee, 1993; *p*. 61). Sargent (1993; *p*. 3) confers these sentiments of scientific experimentation by stating:

> "Rational expectations imposes two requirements on economic models: individual rationality, and mutual consistency of perceptions about the environment… I interpret a proposal to build a model with boundedly rational agents as a call to retreat from the second piece of rational expectations (mutual consistency of perceptions) by expelling rational agents from our model environments and replacing them with artificially intelligent agents who behave like 'econometricians'. These econometricians theorize, estimate and adapt in attempting to learn about probability distributions which, under rational expectations they already know".

There are two distinguishable strategies of scientific experimentation for model building to which *ADEM* may be undertaken, termed 'active' and 'passive' *ADEM* (Holling, 1978; Walters, 1986). Active *ADEM* is considered a 'learning-by-doing' approach whereby the resource manager designs experiments so as to deliberately perturb and manipulate the ecosystem in order to decipher its ecological response in accordance with the hypothetico-deductive method of research. Briefly, the hypothetico-deductive method states that the resource manager is required to test a hypothesis (*i.e*. a system state) indirectly by deriving from it predictions. These predictions are amenable to empirical examination, and if the predictions are borne out by the data, then that result is taken as a confirming instance of the hypothesis (see Figure 4).

Figure 4: The hypothetico-deductive method that underpins active *ADEM*.



Whilst the hypothetico-deductive method is utilized by active *ADEM*, it is not the precise process of performing scientific experiments as observed in controlled laboratory conditions. A critical difference between science and active *ADEM* modeling is the type and degree of 'risk in interpretation' that each is willing to accept (Lee, 1993). Accordingly, while in science the burden of proof is tilted toward highly reliable findings with p values of less than '0.05', this is not the case with active *ADEM* modeling where even p values of less than '0.5' are considered of use (Lee, 1999). After all, as Lee (1993; *p*. 53) rightly states:

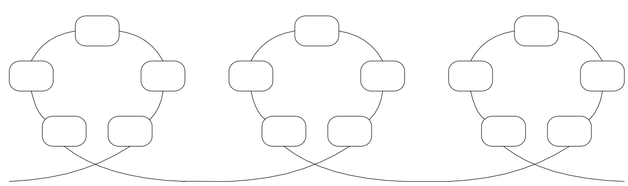
> "If the policy succeeds, the hypothesis is affirmed. But if the policy fails, an adaptive design still permits learning, so that future [evaluations] can proceed from a better base of understanding".

Passive *ADEM*, quite unlike active *ADEM*, is best considered a 'learning-by-observing' approach because it does not involve any experimental manipulation. Instead, passive *ADEM* maintains its scientific rigour by administering what has been described as 'natural experiments' through careful observation, which enable the resource manager to come to fruitful generalizations without intervening directly themselves. Thus, passive *ADEM* is underpinned by a quantitative inductive research method in that it makes inferences about the whole ecosystem from the quantitative properties of the sample data.

To that end, Holling (1978) proclaims that active *ADEM* should guide ecosystem management because it is likely to provide more reliable results leading to greater levels of learning than passive *ADEM*. This argument is reasonable as to overcome the well-known problems of induction; we might well focus on 'Popperian falsification' by utilizing the hypothetico-deductive method. However, in reality which *ADEM* strategy is utilized depends on the economic payoffs involved as there is always trade-offs between the 'costs of deliberation and information' and 'precision' (Pitz & Sachs, 1984; Conlisk, 1996). Hence, active *ADEM* which is inherently more costly because of direct experimentation (Walters *et al*., 1993; Lee, 1999), would only be considered an economically viable strategy if both the probability of gaining information and the expected benefits of the information were deemed substantial (Failing *et al*., 2004).

Regardless of whether active or passive *ADEM* is utilized, systematic errors are retained in the model building process in either strategy (Fitzgibbons, 1995; Walters, 1997; Norton, 1999; 2005). Thus, model building is not a once off process, but is a process of continuous iterative learning (see Figure 5), whereby models are built, refined and adapted as updated localized information is gleaned from ongoing research (Lempert *et al*., 1996).

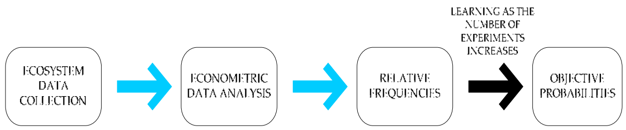
Figure 5: The continuous iterative process of learning (Adapted from Margoluis & Salafsky, 1998).



3.1 Ambiguity and Ignorance

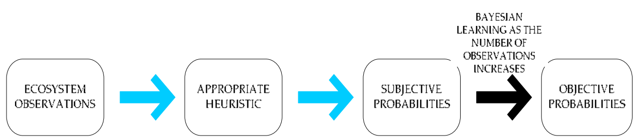
Given the differing strategies of experimentation of active and passive *ADEM*, it is intuitive to envisage that active and passive *ADEM* are dispositioned for economic evaluation towards von Neumann and Morgenstern's (1944; 1953) expected utility theory and Savage's (1954) subjective expected utility theory, respectively. Comprehending these methodological connections is straightforward, as von Neumann and Morgenstern expected utility theory like active *ADEM* assumes that objectively determined statistical probabilities or relative frequencies, are determined from random sample experiments. Evidently then, learning can occur as the number of experiments are repeated over time, allowing relative frequencies to presumably converge towards the limiting relative frequencies of system state space (see Figure 6).

Figure 6: Von Neumann and Morgenstern expected utility theory for active *ADEM*.



Similarly, passive *ADEM* is appropriately modeled by subjective expected utility theory because the theory attempts to convey probabilities of system states not in any objective sense, but rather by the resource manager's own subjective plausibility of events developed from observation. Hence, these subjective probabilities depict the resource manager's degrees of 'belief' of the likelihood of a system state occurring, even when no random sampling process of any kind is involved (Savage, 1954). Hence, because probabilities are subjective, it is likely that there will be different elicited subjective probabilities given by different resource managers for the same system states and information available. This phenonmena occurs in part because when resource managers are faced with the task of determining subjective probabilities, they employ the quite personalized method of heuristics (Tversky & Kahneman, 1973; 1974). Nevertheless, despite these differences of subjectivity over time subjective probabilities with adjustment and refinement resultant from learning as the number of observations increases, in the inductive Bayesian statistics tradition, will it is reasoned see subjective probabilities converge onto objective probabilities, if only asymptotically (see Figure 7).

Figure 7: Subjective expected utility theory for passive *ADEM*.



Fishburn (1970; *p*. 191) interestingly once described subjective expected utility theory as "the most brilliant axiomatic theory of utility ever developed". Such praise might be warranted if one considers that with subjective probabilities, the 'bane of neoclassical economics', Knight's (1921) famous division of risk and ambiguity as neoclassical economists understand Knightian uncertainty, could once and for all be laid to rest. This is because ambiguity (see Ellsberg, 1961), defined as "uncertainty about probability, created from missing information that is relevant and could be known" (Camerer & Weber, 1992; *p*. 330), could now be unraveled in that an ill-defined relative frequency could instantly be assigned a quantifiable subjective probability instead. Hence, subjective probabilities allow ambiguity or the 'hypothetical risk of risk', to be collapsed back into the mathematically tractable terms of mere risk.

This neoclassical resolution of Knightian uncertainty can be characterized as the difference between the actions of 'prevention' and 'precaution', which are terms of importance to ecosystem management. This is reasoned because subjective probabilities permit the ‘precautionary principle’, which states that a lack of full scientific certainty should not be used as a reason to postpone ecosystem management, to be quantitatively determined. It is this ability to measure the precautionary principle through subjective probabilities, which permits not only the use of meaningful economic analysis, but prevents a series of seemingly perverse economic consequences from occurring, whereby the costs of acting on precautionary measures well exceed the costs of waiting until the hypothetical risks of precaution are resolved (Prato, 1998).

However, where no probabilities exist *a posteriori*, Bayesian statisticians would argue that *a priori* probabilities can still be elicited, despite them being criticized because such probabilities often have no scientific standing (Schmeidler, 1989). Fortunately, even where ambiguity of the probability distribution of outcomes remains persistent, it is still possible to evaluate through the principle of insufficient reason or more effectively through the utilization of the ‘safe minimum standard’ (Ciriacy-Wantrap, 1952; 1968). Of economic importance, the safe minimum standard replicates the same problems faced within the game theoretic ‘minimax’ criterion, which states that the resource manager should ‘choose’ the system state that minimizes the maximum loss (Bishop, 1978).

The resource manager under ignorance can nevertheless, despite contravening the demands of the precautionary principle, adopt Hick’s (1974) neoclassical interpretation of Keynes’s liquidity preference, which contends that it is rational to postpone the economic evaluation and the system state adoption until further learning has subsequently taken place (Pasinetti, 1981; Kreps, 1988; Abadi-Graham & Pannell, 2001). For example, let us assume two periods of discrete time, with ignorance in period t_1, which is resolved in period t_2. If the economic evaluation takes place in t_1, then public funds K is used to manage the system into the preferred system state before the resolution of the ignorance, which results in a loss of economic flexibility. However, if K is used for the preferred system state in t_2, then the resource manager retains the flexibility to cope with surprises.

3.2 Adaptive Expectations and Ergodicity

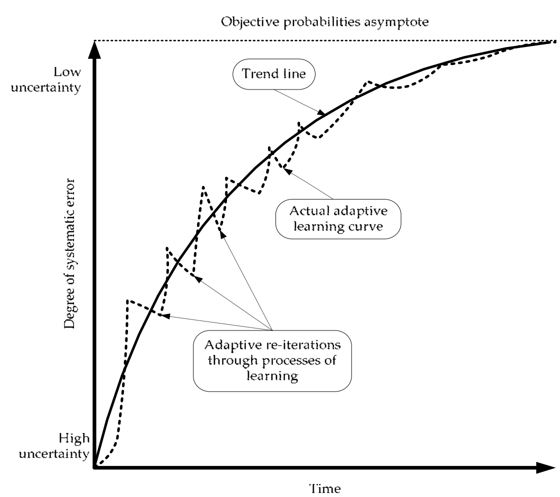
In acknowledging the foundations of *ADEM*, we can suggest a model of the expectations of the resource manager. In doing this, we immediately can ask some fundamental questions. In particular, what are the expectations of those who behave like an econometrician, and what would the consequences of the model of expectations be when extended to its logical end? Now, to answer these questions we need to recapitulate that rational expectations as presumed in *ANEM* restricts evaluation rules by adopting the assumptions of optimization and the consistency of perceptions. However, in descriptive environments bounded rationality results in both assumptions being dropped, while in the prescriptive environment of *ADEM*, we need only drop the second assumption, and replace it with a model for representing and updating rules of evaluation (Sargent, 1993).

To that end, there have been various attempts to incorporate the expectations of econometricians, including the use of computational adaptive algorithms (see Arifovic, 1994). However, despite this the most prominent approach is the relatively simple adaptive expectations hypothesis, which while showing only marginal explanatory success (Lawson, 1994), has some empirical support for it in controlled environments (Smith *et al*., 1988; Ramon *et al*., 1993; Hey, 1994).

Explicitly, adaptive expectations states that the resource manager's forecast, should be adjusted and revised approximately by the amount proportional to the previous evaluation's observed forecast error. Thus, adaptive expectations maintains that forecasts of the probabilities of the set of system states are based on historical information, indicating that unlike rational expectations a measure of learning is incorporated explicitly. After all, unlike rational expectations, adaptive expectations are assumed to be a statistical shadow of past and present signals. Moreover, employing the use of historical information makes the adaptive expectations hypothesis structurally sound, since epistemologically speaking, forecasts and expectations can only be based from actual experience (Palley, 1993).

As we know, the resource manager is prevented from using existing information to fully obtain short-term knowledge regarding the probabilities of future system states. However, over time as systematic error is reduced because of learning it is envisaged to converge onto the ecosystem's objective probability distribution (see Figure 8). This supposed convergence towards objective probabilities is "a kind of foreshadowing of the rational expectations theory that assumes an ultimate validity to the concept of objective probability" (Rosser, 2001; *p*. 13).

Figure 8: *ADEM* is theorized to lead towards the convergence onto an objective probabilities asymptote.



Whilst some economists remain cautious about claiming support for rational expectations on the grounds of learning by adaptive expectations (see Blume & Easley, 1982; Bray & Kreps, 1987), at least theoretically, it is reasonable to argue that in the long-term utility optimization in logical time as found in *ANEM* could take the place of

ADEM. Accordingly, if this were so then, "[*ADEM*] offers the hope that by learning from experience we can reach and maintain a managed equilibrium" (Lee, 1993; *p*. 58).

One can conclude then that the focus of *ADEM* is on the process of equilibration towards the equilibrium of rational expectations, which may be lengthy because of our bounded rationality, while *ANEM* focuses solely around this equilibrium horizon. As a consequence, unlike equilibrium analysis underpinning *ANEM*, *ADEM* is best underpinned by disequilibrium analysis in that present information is imperfect and some of it wrong that modelling may proceed on a non-steady state path. However, over time as learning occurs, the steady state path may be revealed allowing for convergence.

The temporary nature of a problematic environment not only exists where learning is outwardly present, as with *ADEM*, but it is theorized by neoclassical economists that even where learning is far less cognizant and analytical the same result will follow. Indeed, even 'learning' based on the random evolutionary mechanisms of Darwinian natural selection, such as that found with trial-and-error and descriptive heuristics, will presumably in the very long-term also show convergence towards global rationality (Todd & Hammerstein, 2001). It seems that natural selection is a powerful optimizing force (see Friedman, 1953). For that reason, it is not that *ADEM* allows the elimination of uncertainty that is so advantageous, but rather it is the increased equilibration rate of convergence that truly differentiates the approach. The rate of convergence is crucial because for optimization to hold, the rate of convergence must be higher than the ecological rate of change from disturbance events (Dosi *et al*., 1999).

An immediate ramification of this convergence onto objective probabilities is that the environment must be considered ergodic, because the system is shown to have a unique long-term equilibrium independent of initial conditions, hence indicating that even where stochasticity is present the system is in fact 'predetermined' (Davidson, 1991; 1996). Hence, ergodicity is not confined simply to those unproblematic deductions made by the globally rational resource manager, but include also bounded rationality, as once epistemic problems are solved, an unproblematic ergodic environment is revealed exhibiting only objective probabilities subject to stochastic variation. This means that all change to the system originates exogenous to the system investigated. As a result, knowledge of the future involves projecting averages based on past or present realizations. The future is merely the statistical reflection of the past.

Importantly, the acceptance of ergodicity is rationalized by neoclassical economists in particular, because it allows for the 'necessity' of developing economics as a science based on certain generalizable laws or event regularities (Samuelson, 1969; Lucas & Sargent, 1981; Solow, 1985). In turn, these generalizable laws of nature justify the use of equilibrium (and disequilibrium) analysis by allowing its presentation by a single formal model that can be subsequently tested by time-series econometrics. Of importance, equilibrium analysis is reductionistic, whereby the all variables and interactions among them in the models built are assumed to be stable and knowable. It is this assumption that provides equilibrium analysis its predictive power in determining future system states. Hence, the underlying ontology in this ergodic environment is that of ecological atomism, often referred to as methodological individualism, whereby an ecosystem is thus a mere epistemic phenomenon generated from additive upward causality of its constituent units (species or even genes).

3.3 Chaos and Complexity

Probability theory is not the 'last word' when modeling uncertainty for economic evaluations and analysis irrespective of the claims by neoclassical economists that with the advent of subjective probabilities all hurdles involving Knightian uncertainty had been laid to rest. However, "it is safe to say that … Knight is more widely quoted than read on his eponymous distinction between risk and uncertainty" (Runde, 1998; *p*. 539).

Importantly, we have stated previously that ecosystems are governed by non-linear dynamics. Interestingly, non-linearities modeled in Hamiltonian systems, render a 'sea of chaos', within its equilibrium construction (see Lorenz, 1993). The presence of so-called 'Hamiltonian chaos' obtained within systems that are computationally complex (*i.e*. first order complexity), indicates that no matter how rational the resource manager might be, they cannot have perfect knowledge of the ecosystem, for the same reason that Gödel (1931) identified that no axiomatic system of deductive logic can be perfectly complete within itself. However, if this finding is not devastating enough to the entertainment of rational expectations (see Grandmont, 1985) and *ANEM*; ecosystems cannot be modeled as energy-conserving Hamiltonian systems either, as they are fully dissipative systems in accordance with the second law of thermodynamics. Indeed, not only must there be a linear and non-linear differentiation in system dynamics, but there must also be a thermodynamic differentiation between systems near and far from equilibrium. As Nicolis and Prigogine (1989; *p*.59) put it "without the maintenance of an appropriate distance from equilibrium, nonlinearity cannot by itself give rise to multiple [system states]".

The dissipative nature of ecosystems it seems would lead us to rather pessimistic conclusions of decay and degradation. However, we observe that decay towards thermodynamic equilibrium is in stark contrast to ecosystem development. But, one is left wondering how do ecosystems build up and maintain complex structures in the face of the second law of thermodynamics? It would appear there is a paradox of nature.

This paradox can be unraveled, nonetheless, because ecosystems are not characterized by non-existent or weak and fixed connections between its constituent units, but instead by strong, non-linear connections, so that ecosystem behaviour can in no way be obtained from simply summing up constituent behaviour (Costanza, 1992; Rastetter *et al*., 1992; Holland, 1998; Kay & Regier, 2000; Potts, 2000*a*). Thus, while it might be reasonable to assemble a mechanical system from its various constituent units, with ecosystems its units are so inter-related that they are expressions of the whole system. For example, a river is not made from 'glued' water and vortices, but rather, the vortex, while 'stable' is an aspect of the river in its entirety (Peat, 2002).

Now, these connective non-linearities develop emergent higher formed structures through a process of self-organization, which progresses the system far-from-equilibrium, so that the system itself must be considered complex not just computationally, but structurally (*i.e*. second order complexity). The dynamics of self-

organization is largely a function of internal causality, so that the system is dominated by non-Newtonian positive and negative feedback loops. Hence, downward causation is real (Kauffman, 2000). Thus, philosophically speaking, decay is avoided, as the dynamic stability of an emergent ecosystem is guaranteed by a 'balance' between processes of dissipation and non-linearity.
The only analogous concept to that of equilibrium found in structurally complex systems is the 'attractor', the basin of attraction for which the system self-organizes about within the actualized system state. But, the conception of the attractor does away with the notion of an equilibrium construct with an ecosystem, because while there are some metaphorical similarities, with an attractor there is no structural stability found at these conditions.

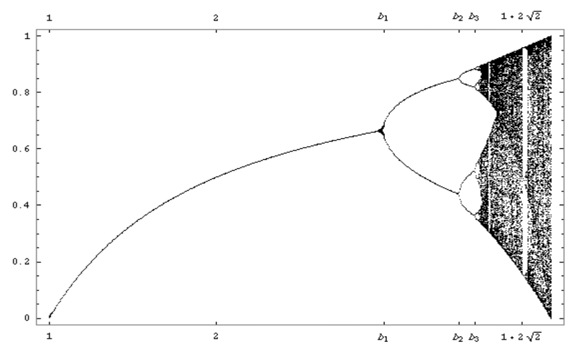
What we have yet to be fully aware of about complex systems, is that beyond a point of self-organized criticality, that is, a threshold value poised at the 'edge of chaos' (Kauffman, 1993), the organizational connective capacity of the system can be overwhelmed and the behaviour of the system becomes highly unstable, whereby the system state can 'endogenously' leave its present basin of attraction. To appreciate this notion of self-organized criticality, another appealing analogy is that of a sand pile, which may represent the development of an ecosystem (see Bak *et al*., 1993; 1996).

Imagine if you will that a thin stream of sand particles is being trickled onto a dish-like object, which represents thermodynamic equilibrium. Over time, a sand pile will steadily develop as the system moves away from equilibrium. As the sand continues to be trickled, a low pile of sand will form, which will gradually get higher and higher in a canonical fashion, until suddenly more sand may trigger a small sand slide, and then say a catastrophic one. Thus, we observe that the same magnitude of disturbance (another grain of sand) may lead to a response of all size ranges. Hence, the distribution of these sand slides effectively follows a power law; that is, even when the pattern of the sand dropping is random and normally distributed the distribution of the sand slides will exhibit greater variance than the distribution of the sand dropping itself. This clarifies why some innocuous ecological changes lead to minor events, while at other times the similar ecological changes lead to major catastrophes.

We now know that as the density of connections increases, so too does the dynamic instability of the system, which is generated internally from the greater extent of positive and negative feedback. Hence, as a system moves towards its attractor and as the number of connections concurrently increases so does its potential towards catastrophic endogenous change towards an alternative system state. Needless to say, but the state attractor can never be reached, because by that stage the state conditions would have changed, so that a state transition would have occurred (Jorgensen, 1997). Therefore, connections which make complex systems stable and robust, at least initially, are also exactly what make them ever so susceptible to change ultimately. Accordingly, as expressed by Ulanowicz (1997), there is a 'window of vitality' or minimum and maximum level in which self-organization can occur. Too much or too little of each of these opposing internal and external forces generate an imbalance which will upset system efficiency. Thus, an optimal operating point exists where environmental disorganizing forces and ecosystem organizing forces are balanced (Kay, 1991).

The dynamic process of state transitions has been captured by bifurcation theory. The general approach of bifurcation theory is to construct symmetry-breaking transitions, that is, bifurcations, which are critical points whereby the system trajectory is divided into alternative pathways. There is a sequence, for example (see Figure 9), that begins with a point attractor which, at a critical value of a control parameter, becomes unstable and bifurcates into another two such attractors, or it may bifurcate into a periodic attractor. It may then at another critical value undergo a sequence of instabilities which transform it into strange chaotic attractor. Importantly, this cascade of symmetry-breaking bifurcations is not just a metaphor, as it is observed empirically in the well-studied patterns of hydrodynamic flow experiments.

Figure 9: A typical non-linear logistic map of the behaviour of complex systems, illustrating the cascade of symmetry-breaking bifurcations leading to chaos.



Where 1 and 2 represent a steady state trajectory;
b_1 represents a bifurcation point at the 'edge of chaos';
b_2 represents the region of multiple bifurcations;
b_3 region of chaos; and
$1 + 2\sqrt{2}$ ('white stripe') represents a chaotic attractor.

Interestingly, the presence of chaotic attractors highlights two important points. First, chaos is not simply the presence of stochastic occurrences, as these random forms have no attractors, whatsoever. Secondly, and ironically, not only is chaos behind the depths of order, but remarkably there is within the depths of chaos, an intricate 'order'. Chaos and order are thus intimately entwined (Prigogine & Stengers, 1984; Kauffman, 1991; Peat, 2002).

3.4 Chaotic Uncertainty

Despite chaos revealing an intricate order, the behaviour of a complex system at the point of bifurcation has elements of historical happenstance, so as to be quantitatively unpredictable. This is because complex systems in the presence of chaos are very dependent upon initial conditions, so that even infinitesimal differences over time between two system states will evolve exponentially from one another, so that over time they are no more alike than any two states selected at random. This is chaotic uncertainty.

Consequently, the prediction of system states in the future certainly cannot be quantified into probabilities, because no matter how rational we might believe we are or how much information we accrue, even the slightest difference generates unpredictability. Thus, in the vicinity of a bifurcation, structural fluctuations with a distinct 'chance-like' character play a dominant role in determining the future system state, so that there is no means in determining near the point of bifurcation, which new system state will be actualized prior to the actual selection occurring. From what we now know, we can only conclude that chaotic behaviour obviates any usefulness of probability and the equilibrium construct for economic evaluations. As such, the aspiration that underlies neoclassical economics of being able to quantitatively predict the system states of the future would appear to be irreconcilable with the modeling of complex systems (Kay *et al*., 1999; Kay & Regier, 2000).

But, is this truly so, after all, what is the ultimate source of chaotic uncertainty? Is chaotic uncertainty simply the result of difficulties in discerning precise values when gathering data and limits on the resource manager's computational capacity, or is it a function of the ecosystem structure itself derived from ontological foundations. The implication of the latter, of course, is that the epistemological problem cannot ultimately be overcome; it is inherent in the very nature of complex systems. However, if it is epistemological, then it is possible that through improvements in *ADEM* by presumably better theory construction, data gathering, or computational capacity that the uncertainties that accrue from chaos can unravel back into problems specific of ignorance, learning and bounded rationality in general (Rosser, 2004).

Whilst there have numerous opinions on this matter (*e.g* Davidson, 1996; McIntyre, 1997; Rosser, 1998; 1999; 2004; Dupuy, 2004), we can now evaluate this discussion in some detail. What is generally agreed upon is that chaotic uncertainty has no ontological foundation, and is merely a problem of epistemology caused because of a lack of computational capacity (see Davidson, 1996). While this conclusion is not a given, it would seem reasonable as if chaotic uncertainty were a truly ontological phenomenon, then at the very least we would need considerable evidence of such phenomena occurring empirically beyond say what has been observed in experiments of hydrodynamic flow (McIntyre, 1997; Delanda, 2002). So, given that chaotic uncertainty is considered an epistemological uncertainty, it could be easy to conclude that overtime these problems of being unable to quantitatively predict can be resolved. However, resolve chaotic uncertainty would require truly exact and perfect information of the investigated complex system, which would in turn require an infinitely high information cost, because no matter how precise the resource manager's measurements and data collection are, even a slight error could lead to completely inaccurate predictions.

As a result, whilst chaotic uncertainty is an epistemological problem, it is reasonable to interpret it as an ontological phenomenon, because chaotic uncertainty can only be solved by an 'infinite economic agent' because an infinite exactness of knowledge, which is problematic in itself (see Gödel, 1931), is required to understand the system (Rosser, 1998; 1999; 2004; Dupuy, 2004). That is, we can construe then that "ecosystems are not only more complex than we think, but more complex than we can think" (Egler, 1977; *p*. 11). Thus, we should treat chaotic uncertainty as a quasiontological uncertainty, even though this uncertainty can in theory vanish, if not in practice. Hence, we should not confuse ignorance with chaotic uncertainty despite their similar economic implications of, to some degree, rejecting utility maximization and considering choice real (Potts, 2000*b*; Dunn, 2001; Rosser, 2001).

But, even if we do not solve our bounded rationality analytically, what about the notion that natural selection is an optimizing force? Needless to say to any ecologist or biologist, but this conception that natural selection leads to optimization is an erroneous neoclassical interpretation of Darwinian evolution (Sober, 1993), which in fact actually better resembles the defunct Lamarckian position of evolutionary perfectionism. Indeed, this optimizing notion of natural selection was appropriated we suspect simply to justify as-if optimization and convergence onto rational expectations. Yet, it is apparent that natural selection is far from an optimizing force (Hodgson, 1993; 1994; Vromen, 1995), and thus, the definition of the long-term as an asymptotic end state of a process of equilibration requires immediate revision.

As a consequence, the true failure of *ADEM* is not as often proclaimed in its diagnosis that there is a need to merely educate resource managers of its processes of analytical learning (*e.g*. Halbert, 1993; McLain & Lee, 1996; Roe, 1996; Walters, 1997, Johnson, 1999). Rather, the underlying failure of *ADEM* is its inability to acknowledge and manage the complexities of ecosystems, despite superfluous claims stating otherwise (*e.g*. Meffe *et al*., 1996; Dempster, 1997; Lee, 1999).

Neoclassical economics, thus, maybe beneficial at prediction of future system states where the system itself is ‘simple’. This is because, inevitably, models are for pragmatic reasons simple, as they attempt to develop a simpler caricature of the system investigated, by removing extraneous information while retaining the essential system characteristics. It is then hoped that the model will predict what the future system states are likely to be. But, this process of model building is not seen as useful when modeling complex systems, as one cannot simplify complex systems into simple models so as to allow for quantitative prediction.

Yet, despite these findings, neoclassical economists continue to place importance on constituent units and equilibrium and not on the importance of connections between the constituent units and far-from-equilibrium phenomena, as they insist on making very strong and unrealistic assumptions about systems so as to allow for deductive equilibrium analysis and mathematical tractability to hold (Lawson, 1997; Foster, 2004). There is obviously an irresistible attraction and deep psychological need for neoclassical economists to only utilize methodological perspectives that are consistent with the notion of an equilibrium construct (Kaldor, 1972), that “silent hum of a perfectly running machine” (Robinson, 1962; *p*. 77). But, this undue fascination with equilibrium has unfortunately been devastating to economics, as it has lead economists to be loathsome to investigate alternative methodologies of economic evaluation.

4.0 Capacitive Ecosystem Management

We can duly surmise that the interpretation of the dynamics of complex systems is an activity in 'double-dealing', in that attempting to manage complex systems demands foreknowledge, but, which is unfortunately precluded because of the chaotic behaviour of complex systems. Indeed, we must it seems forever forgo the belief of prediction, the 'canon' of neoclassical economic theory. Hence, we need to turn to an alternative post-classical economic analysis, in which the analytical foundations of equilibrium and probability are not utilized. After all, the ramifications of complexity and chaos have led us to re-examine how we might undertake economic evaluations and manage our ecosystems.

Since complex systems thwart the resource manager from ever knowing, even probabilistically, what system state in the future will actually transpire, it at once appears that an approach for ecosystem management should not be focused on deciphering the most desirable system state *per se*, but rather on progressing the ability to 'react' and 'adapt' to ecologies that are forever-changing (*e.g*. Reid, 1994; Lempert *et al*., 1996; Levin, 1999; Anderies, 2002; Berkes *et al*., 2003; Olsson *et al*., 2004). In other words, the only appropriate means to proceed in an environment that is chaotically uncertain is to provide it capacity to adapt to change. This approach has been articulated as 'adaptive capacity', and is the underlying strategy to what we express as 'capacitive ecosystem management' (*CAEM*).

In view of the fact that change in complex systems lessens the effectiveness of being well-adapted to present ecological conditions so as to fully exploit them, it makes economic sense to strategize for change by improving adaptive capacity. To improve adaptive capacity, we need flexibility in our institutions (see North, 1995). Thus, once the adaptation state space is understood, society can build institutional flexibility by preparing and developing the necessary managerial responses and contingencies under the various perceived ecological challenges considered. This will allow the greatest possible adaptation to the myriad of potential ecological changes, so as to minimize the possibilities of surprise and ecological catastrophe (Fankhauser *et al*., 1999; Walker *et al*., 2002).

Successful adaptation resultant from ecological change requires three attributes to develop institutional flexibility: first, the timely recognition of the need to adapt; secondly, the economic incentive to adapt; and thirdly, the institutional ability to adapt. Effectively then, the existence of institutions that learn and store knowledge and information while developing flexibility, so that institutional structures match the processes of ecosystems in a 'co-evolutionary' fashion (see Norgaard, 1990; 1994; Erickson, 1999; Gowdy & Erickson, 2005), is critical to the successful undertaking of an adaptive capacity strategy (Folke *et al*., 1998; Scheffer *et al*., 2000; Berkes *et al*., 2002). Without a doubt, an error of ecosystems that equals that of the erroneous assumption of prediction is the mistaken assumption that ecosystems can be treated independently from economic systems that utilize and analyse these 'natural' systems. In fact, there is now much evidence to suggest that *ADEM* failed repeatedly because the existing institutional structures utilized had not allowed it to function effectively under ever-changing ecological conditions (Folke *et al*., 2002; Walker *et al*., 2004).

At this juncture, it is feasible to state the requisites required for *CAEM* (see Hollick, 1993). These are: one, that institutional flexibility is maximised; two, that knowledge and understanding is sort concerning the non-linear dynamics of endogenous change of complex systems; three, that practices that interpret and respond to ecological feedback (positive and negative) are incorporated to modelling protocols; and four, that frequent incremental adjustments are made to the complex system rather than a few major managerial shocks, so as to potentially 'humble' the believed 'negative' effects of chaos by forestalling lets say 'ecosystem pressure', and to avoid large catastrophic bifurcations, which might lead from flipping into one chaotic attractor to the next (Folkes *et al*., 1998; 2003).

Interestingly, a closer inspection of adaptive capacity reveals the legitimacy of this strategy, because in advancing flexibility we seem to be emulating how nature-itself combats the 'problems' of unpredictability ensuing from chaotic uncertainty. Indeed, while ecology as a field of study has had a controversial history in postulating the underlying functionality of biodiversity, it seems that a plausible explanation is that where co-dependencies are not overwhelming, diversity may well afford the maintenance of adaptive capacity within the ecosystem-itself (*e.g*. Risser, 1995; Tilman, 1996; Grime, 1998; Peterson *et al*., 1998; Naeem *et al*., 2000; Lehman & Tilman, 2000; Carpenter *et al*., 2001*a*; Bengtsson *et al*., 2002; Folke *et al*., 2003). This explanation for the role of diversity certainly would rationalize the excess or functional redundancy of species that exists. Indeed, there seem to be a positive correlation between diversity and redundancy, so that diversity can be considered an 'uncertainty-diffusion mechanism' (Folke *et al*., 2003).

Nevertheless, regardless of these valid ecological arguments, some neoclassical economists might further criticize adaptive capacity on evolutionary grounds in that economic inefficiencies resultant from institutional flexibility will in the long-term lead to an inability to 'endure', in keeping with the evolutionary conception of 'natural selection' and the memorable aphorism of the 'survival of the fittest', which presumably demonstrates that 'efficient' utility-driven strategies will ultimately out last 'inefficient' strategies relating to flexibility. However, this evolutionary inference is a (somewhat) mistaken assessment of how Darwin (1859) himself wished his theory of natural selection to be interpreted. It is not in fact the strongest that survive according to Darwinian evolutionary theory, but rather it is those that adapt to change that 'survive'. Indeed, Darwin (1869) did not simply imply these sentiments, but stated them explicitly: "It is not the strongest of the species that survives, not the most intelligent, but the most responsive to change". As such, those that actually struggle to survive are not the weakest *per se*, but those unable to adapt to change. Thus, it is little wonder that natural selection is not an optimizing force, as understood previously, as it is not 'survival of the fittest' that matters, but rather, adaptive capacity.

4.1 Exploration and Simulation

To recapitulate, economically speaking, *CAEM* is not about focusing on the most desirable system states at a single point in time, but rather, it is about focusing our attention on possible 'economic efficiencies' at future points in time. Consequently, what we are effectively looking to achieve is to maximize flexibility through contingency building across the exhaustive set of system states, rather than maximize utility for a particular system state. Thus, we are shifting focus from an analytical equilibrium construct, which focused on the need for efficient allocation, to a post-classical analytical construct, here termed 'analytical multiplicity' that effectively incorporates the processes of adaptation and not equilibration, and the need for excess capacity.

We now know that economic evaluations by *CAEM* must commence with the recognition that associated probabilities for system states are indeterminable. Likewise, while the set of system states is considered determinable, because of bounded rationality we cannot assume that the resource manager has access to this exhaustive set *a priori*. Thus, the resource manager guided by *CAEM* must first and foremost 'explore' state space (Bradbury, 2002). Through exploration it is hoped that we can replicate the dynamics of complex systems by utilizing multi-agent simulations, which are able to model the non-linear dynamics of ecosystems. Hence, these simulations allow the resource manager to explore computationally the various possible trajectories so as to establish the exhaustive set of system states.

Again, we need to iterate, that it is imperative to recognize that simulations utilized for exploration, are certainly not intended as a proxy for prediction. On the contrary, exploration is not about a meager attempt to predict and then gamble on the likelihood of future system states at all. Rather, exploration is only about enhancing ecological understanding of the set of system states available. Thus, adaptive capacity does not attempt to predict the actualized outcome of adaptation, rather it "in effect gives a picture of the adaptation space within which adaptation is feasible" (Adger & Vincent, 2005; *p*. 400).

As a consequence, in theories of economic change we can make a distinction between 'exploitation' and 'exploration' (Holland, 1975; March, 1991), which are to all intents and purposes associated with first-order and second-order learning, respectively (see Bateson, 1973; 1987; Fiol & Lyles, 1985). Therefore, whereas *ADEM* is about first-order learning by way of improving the processes of equilibration towards complete exploitation, *CAEM* and adaptive capacity are about second-order learning by improving processes of adaptation for exploration in determining state space.

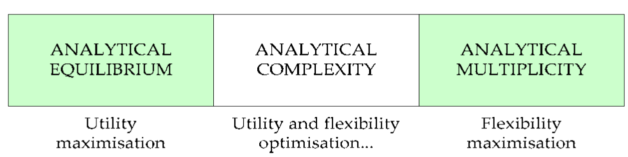
4.2 Analytical Complexity

Despite adaptive capacity as a management strategy attempting to maximize flexibility, it might well be criticized amongst other things by neoclassical economists for resulting in the significant accumulation of sunk costs involved in a seemingly excess-driven and inefficient approach to ecosystem management. After all, in designing a strategy that spreads its scope and its responsiveness potentially to all system states in state space, there is an immediate resignation towards economic sub-optimality because of the necessary neglect for the present actualized system state. Indeed, while we know that the more we invest in a particular system state, the less the system might be suited to changes in the future. All the same, we also know that the converse must also be true. That is, the more we prepare for future contingences, the less we have devoted ourselves to the present. Thus, while maintaining flexibility may allow the system to adapt and allow for ‘survival’, ecosystem management is more than mere caution for survival, but also the production of utility.

Consequently, there is an economic trade-off between the maximization of flexibility and utility. But, how does one decide the ‘dynamic balance’ between the known present and the exhaustive set of system states of the future, when the actuality of future system states remain unknowable? It is this economic problem that neoclassical economic theory has never acknowledged and yet this very problem of a dynamic balance seems critical to economic evaluations (Potts, 2000*a*). Therefore, what we do know is that when undertaking economic evaluations we should never be overly cautious through flexibility maximization or risk-taking through utility maximization, because this is neither sound economically or ecologically.

Economic efficiency of the genuine kind, must be viewed as an economic efficiency in the context of historical time, and as such, is the dynamic balance between these mutually opposing expressions of economic efficiency (*i.e*. analytical equilibrium and multiplicity), which we refer to through the naturalistic metaphor as ‘analytical complexity’ (see Figure 10). One can construe then that while analytical equilibrium is the manifestation of a ‘static balance’ in a linear neoclassical environment, analytical complexity can be considered as the manifestation of ‘dynamic balance’ in a non-linear post-classical environment.

Figure 10: The analytical constructs of economic analysis.



Significantly, and by no means coincidently, the workings of analytical complexity in an optimal range of utility and flexibility, may well be exactly the minimum and maximum levels required for the processes of self-organizing to be made possible, so as to allow complexity in an ecosystem to arise. It is reasonable to presume that complexity exists in nature for this very reason, as nature itself faces this very problem, in that it must keep its options open, yet it must maintain some efficiency to gain ‘utility’. One might even suggest that states of complexity poised at the edge of chaos are ‘naturalistic economic evaluators’, as only in states of complexity reflected by the analytical complexity construct are systems attempting to ‘optimize’ dynamically both utility and flexibility.

While Low *et al*. (2003) recently equivocated that little is known about the exact level of system excess or ‘redundancy’ that should exist in a complex system, we know that the resolution of the amount of redundancy we allow for at the time of the economic evaluation must be at the very least be some component between the two extremes found at the analytical equilibrium and the analytical multiplicity. However, we might be able to do better than this because despite the impossibilities of quantitative prediction, or relevance of defining the many system states available (Capra, 1996), we might be better off by an alternative means of inference, as after all, we know that even the behaviour of a complex system in a chaotic regime is not completely erratic. The 'white windows' in the 'black veil' of a chaotic future depicted in *Figure 6* indicate localized phases of order within the sea of chaos. Thus, whilst our ability to predict complex systems is inherently limited quantitatively, it may be possible to develop a metaphorical portrait of the dynamic movements of complex systems through qualitative induction (Rosser, 2004).

Qualitative induction consists in assembling certain qualitative features of a sample of state space in such a way that this combination of features resembles others in certain essential characteristics. Thus, whilst quantitative induction makes inferences about a totality from the quantitative properties of a sample, qualitative induction, in contrast, supplements the observed features of a sample with others that are not perceived. In fact generalized qualitative inductions form into nothing other than heuristics, which thus, indicates qualitative induction as only a weak probabilistic form of inference (see Dequech, 2001).

Of note, given the heuristic nature of determining the optimal range encountered with analytical complexity, one can conclude that this finding solidifies Simon's (1957) satisficing evaluation rule rather than the neoclassical rules of point-like optimization into perpetuity. Needless to say, but satisficing certainly makes sense as an ever-changing ecological and economic environment leaves exact optimization constructs redundant. After all, economic agents must forever face up to their problems of bounded rationality and ecological change.

Nevertheless, despite the satsficing elements for economic evaluation and its weak mode of inference, qualitative induction is still a useful method for recognizing complex phenomena. Indeed, analysis in the bounds of complexity, while needing to utilize models of qualitative data, and build extensively on case study research, will it is foreseen be able to decipher undesirable system states and pathways that should be avoided as much as possible (Berkes *et al*., 2003). In terms of avoiding undesirable system states, much in the manner of the safe minimum standard, it is worth highlighting that the supply of ecosystem goods and services depends more on which configuration the ecosystem is in than on the particular combination of the state variables. Hence, there is likely to be many system states that will provide a satisficing supply of ecosystem goods and services (Walker *et al*., 2002).

A post-classical economic evaluation under the guidance of *CAEM*, thus, would proceed as follows. First, the resource manager would adopt a designated 'payoff period' criterion, based possibly on the notion of economic resilience, a measure of the speculated time taken for a system state to converge towards its attractor. This payoff period will act as a time frame in which the cost of the ecosystem management must be covered by the expected gains in utility that the resource manager believes can be reasonably met. That is, while it cannot know the future system states with any certainty, the resource manager should endeavour to manage system states that provide a reasonable assurance of generating satisficing utility within this time frame of the payoff period. Secondly, the resource manager will attempt to structure itself so that it avoids system states that are surely undesirable (Penrose, 1995; Shapiro, 1997; McKenna & Zannoni, 2000; Walker *et al*., 2002; Berkes *et al*., 2003).

4.3 Open Systems

We know that ecosystems can receive information so that it can translate this information into a sort of 'knowledge structure' if you will, allowing the ecosystem to have some power over the acquisition of energy. This ecological knowledge is of course, nothing other than the capacity to make connections between its constituent units. But, what is now so very important and even striking, is that this knowledge itself is subject to the evolutionary forces of natural selection. Thus, these systems are not just determined by non-linear dynamics as defined by *CAEM*, but by non-linear combinatorics as well, so that these systems are complex adaptive systems (*i.e*. third order complexity), capable of surprising us through creative forces. From our perspective, a major contribution to understanding the processes that occur with complex adaptive system is Holling's (1986; 1992) meta-model, the adaptive cycle, which incorporates implicitly principles of emergence, complexity, evolution, self-organization and creativity, as it mimics the processes of 'creative destruction' coined by Schumpeter (1950).

In an attempt to account for the forces of Darwinian evolution that impose on complex adaptive systems, evolutionary computation has been developed, which contains algorithmically the underlying natural selection mechanisms of random mutation and selection specifically in their computational models. The most well-known of these evolutionary algorithms is the 'genetic algorithm' (Mitchell, 1996). Nevertheless, the task of identifying the myriad of possible system states created by natural selection, even with the help of genetic algorithms, might well seem insurmountable. Nevertheless, even where the number of system states is likely to be vast for the ecosystem investigated, it is still possible to utilize the method of exploration by utilizing 'Monte Carlo analysis', which randomly samples the set of system states by generating random values for unknown system rules, so that a representation of system states are defined.

However, despite the potential usefulness of computationally modeling evolutionary developments in ecosystems artificially, complex adaptive systems previously modeled by genetic algorithms while initially being able to produce a rich diversity, ultimately peter out losing there ability to be truly creative (Standish, 2006). This is because these artificially generated systems developed algorithmically seem to lack the ability to imitate the open-endedness of evolution when creativity is possible. This is conjectured to happen because with any algorithm we need first to pre-state the initial rules of the game. Thus, we cannot compute and pre-state configuration space, because in an open-ended evolution inevitably new rules of the game are created.

Ecosystems as complex adaptive systems, are not algorithmic at all, and hence are outside our capacity to not only ever predict, but even outside the possibility to explore, even if only in a limited way. This inability to explore is not because of chaotic uncertainty or evolution alone, but because of reasons of emergence and creativity in that complex adaptive ecosystems seem to seek to expand their 'adjacent possible' (Kauffman, 2000). As a result, we must stress that while *CAEM* captures post-classical economic sentiments by integrating non-linear dynamics into its far-from-equilibrium analysis, this still does not go far enough; as we can never determine the exhaustive set of system states available in a complex adaptive system, because we can never finitely determine all possible adaptations that might arise. That is, no matter now much exploration is done to ascertain the exhaustive set of system states, the fact remains that the ecosystem is evolving its very own possibilities. Thus, the future state space of an ecosystem is not finite, but infinite and forever open-ended.

An open-ended future, which reflects an open systems ontology (see Lawson, 1997; 2003) is one where the future can never be logically derived from the observations of the past and the present, because the future "has not yet been created" (Capek, 1971; *p*. 106-111). Hence, the future does not reflect the past and as such, complex adaptive systems are not ergodic systems at all, but rather non-ergodic systems that create structural changes (see Davidson, 1991; 1994; 1996; Lewis & Runde, 1999). Instead, as Bergson (1910) articulated many years ago, to model a truly open-ended future found with non-ergodic systems, we must assume that the past and the present are best imagined as 'charged' with an infinite array of creative possibilities creating virtual ecologies of the future, that may or may not become actualized system states. Thus, nature cannot be considered simply the constant change of 'being', but instead it must be considered an unfolding evolutionary process of 'becoming'. An ecosystem is an emerging story (Kauffman, 2000).

Beyond the relations of actualized forces, virtual ecology will not simply attempt to preserve the system state actualized, but will equally want to engender conditions for the creation of unprecedented system state configurations that have never been contemplated whatsoever (Guattari, 1992). Indeed, what we seem to be suggesting is effectively an open-ended analytical complexity is where ecosystems wish to lie, as "all systems of value… install themselves at this … interface between the necessary actual and the possibilist virtual" (Guattari, 1992; *p*. 54-55). The virtual would be as much open to revision or transformation as the actual, such that each time a possibility passed into actuality, the whole domain of the possible would be re-figured.

Accordingly, with this 'historical continuous passage' of forever becoming and emergence, we might well wish to abandon the conception of the long-term in economic evaluations, as it somehow presupposes a sort of steady state of an adjustment process, rather than a future which is categorically non-equilibrium (Dunn, 2001). Moreover, although chaos theory relinquished the usage of equilibrium and probabilities for economic evaluations of complex systems, an open systems ontology not only reinforces this position, but provides an even more fault-finding critique of these neoclassical theories of economic evaluation, as they fundamentally depend on a closed system ontology, that is, an exhaustive set of system states (Keynes, 1937; Shackle, 1955; 1969; Lawson, 1993; 1999; 2003). Indeed, if we remain assuming that ecosystems are only confined to the problems of epistemology, then we must charge this position with what Bhaskar (1978) considers the fundamental mistake of positive ergodic science, termed the ‘epistemic fallacy’, whereby an unconditional failure has been made in adequately sustaining the distinction between ‘phenomena’ relating to epistemology and those of ontology (Lawson, 1997).

4.4 Genuine Uncertainty

We can surmise that the future cannot be known prior to its creation, not even in principle. The future is forever non-ergodic in accordance with an open systems ontology. Therefore, even if the informational processing power and rationality of the resource manager was infinite, and thus was able to solve all problems of complexity, the future direction of nature could still never be known (Dequech, 2001). Thus, knowledge becomes intrinsically incomplete, fallible and remains forever problematic, providing justification for the continuous management of ecosystems. That is, resource managers will remain forever ‘ignorant’ of the extent of the possibilities of the future, because of the irreversible and open-ended nature of the future, which is transmutable and creative. As a result, we must accept another form of uncertainty into economic evaluations, that of genuine uncertainty. The presence of genuine uncertainty, which exists in all ‘crucial’ economic evaluations of any reasonable time period (see Shackle, 1955; Davidson, 1994), should present the resource manager with the belief that during the time between the moment of economic evaluation and the designated payoff period, unforeseeable changes will inevitably occur, no matter the circumstances (see Table 1).

Table 1: The various forms of uncertainty.

Form of Uncertainty	Knowledge of System states	Objective probability Function
Risk	All states in set Known	Probabilities known
Ambiguity	All states in set Known	Probabilities unknown, but knowable
Ignorance	All states unknown, but knowable	Probabilities unknown, but knowable
Chaotic uncertainty	All states unknown; but knowable	Probabilities unknowable
Genuine uncertainty	All states in set Unknowable	Probabilities unknowable

The presence of genuine uncertainty in an open systems ontology, seems to lead to immediate problems of indeterminism, and thus leaving in turn economic evaluations in a state of analytical nihilism (see Coddington, 1982). Reid (1994) also drew these nihilistic conclusions for economic evaluations where genuine uncertainty is present, but unlike Coddington (1982) who dismissed genuine uncertainty out of hand, he argues that genuine uncertainty must be respected because it is an inherent facet of nature. Thus, does this then mean we should forever retire into a pessimistic attitude of 'Heideggerian resignation of nihilism', and accept our seemingly nihilistic fate, and relinquish any attempt to 'manipulate' ecosystems through the findings of economic evaluations?

4.5 Causality and Methodology

Despite the nihilistic foray and ignorance of the resource manager, this does not mean that the resource manager should not at least attempt "… to defeat the dark forces of time and ignorance which envelop… [the] future" (Keynes, 1936; *p*. 155). After all, while it is true that in evaluating complex adaptive systems we are faced with genuine uncertainty, this does not mean that creativity is opposed to deterministic causality, whereby the creativity derives from nothing other than spontaneous processes and chance. Indeed, we must rule this possibility out, as if creativity does not follow scientific laws of causality, we will must accept the quite unsatisfactorily notion of the 'uncaused cause', which would leave scientific projects utterly meaningless, as 'anything goes'. Quite simply, we are obliged to attempt to understand ecosystems and search for causal explanations and determinacy (Hodgson, 2002; 2004).

Interestingly, while it is impossible to disprove the uncaused cause, Kauffman (1993) makes a powerful argument that natural selection alone cannot explain the origin of complex adaptive systems. Systems involving non-linear interactions involve a large number of possible system states, most of which would have little survival value.

Kauffman argues that processes of self-organization found in states of complexity channel systems into more restrictive possibilities, some of which can have evolutionary benefits. Kauffman (1993; *p*. 644) goes on by stating:

> "I have tried to take steps toward characterizing the interaction of selection and self-organization. … Evolution is not jus 'chance caught on the wing'. It is not just tinkering of the *ad hoc*, of bricolage, of contraption. It is emergent order [honoured] and honed by selection".

Indeed, whilst it seems that creativity is a random combinatorial process, this is because of too many uncertainties and chaotic influences enter the creative process (Simonton, 2004). In fact, one should be careful not to assume that chaos is a negative phenomenon, as would be insinuated where creativity and complex adaptive systems are not considered. This is because in states of chaos, a very necessary function is provided, by way of much experimentation at creating possibilities within the potential pool of resources. Nevertheless, while chaos should not be seen negatively, nor should it be seen positively either, as despite its prospective ability for creativity, it is unable to actualize any of these creative forms to allow for utility generation. Needless to say, but the opposite effect occurs in states of order, where utility is maximized, but experimentation of the ecological structure is minimized. Thus, 'utilizable creativity' only emerges in complex adaptive systems in states at the edge of chaos, where there is a balance between utility generation and creativity. Here, this differs in the analytical complexity described previously, as the bounds between future creativity and present exploitation are a 'smudge', rather than a point-like optimum (Potts, 2000*a*).

Now, given the origins of creativity it seems reasonable to investigate causal explanations and determinisms. However, we have already observed that deterministic causality in the form which allows predictability is an unwarrantable type of determinism. These deductive methods of economic evaluation that embrace predictability are founded on intrinsic conditions of closure, so that not only does this presume that the system is closed, but it implies that the ecological cause will always produce the same system state. But, even if the determinism involved simply links one set of ecological causes with one set of systems states, described as 'regularity determinism', there still results in objections to its use. After all, this form of determinism, which is based in inductive logic, involves extrinsic conditions of closure so while the system need not be considered closed, it is methodologically assumed to be closed. It is important to recognize that even when integrating non-linear dynamics into the modeling of ecosystems, that regularity determinism remains present, as it still nevertheless follows that given the exact same initial conditions that the same system state will invariably be the outcome. It follows therefore, that we must reject these forms of deterministic causality as they result in closure and ergodicity, yet, in open systems, the processes involved are always irreversible and therefore forever historical (see Lawson, 1997; Hodgson, 2002).

Despite the open-endedness of complex adaptive systems, we can however acknowledge causal processes through the principle of universal causation, which states simply that 'every system state has a cause' or more precisely, everything is determined in accordance with the laws by something else (Hodgson, 2004). Nevertheless, regardless of the problems of causality in open systems economic evaluations, given the processes involved in spatio-temporal dynamisms governed by attractors are completely deterministic, we may well have to go beyond the deterministic-indeterministic dichotomy, and introduce more advanced determinisms, which lie between these dichotomous extremes. Indeed, Lawson (1997; 2003) has postulated the existence of what might be described as an advanced determinisms, which he coined 'demi-regularities'. Demi-regularities are similar to event regularities found in closed systems, but are only form partial closures. Nevertheless, the existence of demi-regularities would allow scientific investigation and useful economic evaluations to take place.

To pursue an understanding of demi-regularities and hence, causal explanations in open systems, we require a mode of reasoning that embodies know-how, accepts creativity and is capable of delving deeper into the causal nature of things. This can be achieved by intuition alone (see Keynes, 1937; Kauffman, 2000). However, it leaves economic evaluations locked into the inaccessible realms of economic psychology, like that observed with heuristics, and not to a cognizant form of analysis.

On the other hand, there is a long forgotten alternative described as abduction, which is a weak possibilistic form of inference and is concerned with the creative, but scientific process of forming, probing and fishing for causal explanatory hypotheses. Indeed, according to Peirce (1934; *p*. 90), induction "never can originate any idea whatever. No more than can deduction. All the ideas of science come to it by the way of abduction". Indeed, abduction is creative, because it infers after the resource manager is genuinely surprised and required a novel explanation to make sense of it all (Reichertz, 2004). Thus, because abduction acts to be creative, and because ecosystems are creative, then despite the claims by Gigerenzer (2004) that descriptive heuristics embodies an 'ecological rationality' this must be erroneous. As while heuristics are adapted to their environment, so still impose inductive logic not only in their development, but in their reasoning, and this then assumes a closed system ontology. Only, abduction and intuition embody an ecological rationality and thus only these methods of economic evaluation should be utilized to determining the pathways of ecosystems in the future (see Table 2)

Table 2: The various modes of inference.

DEDUCTION	QUANTITATIVE INDUCTION	QUALITATIVE INDUCTION	ABDUCTION	INTUITION
Certain mode of logical inference and a valid form of the logic of justification	Limiting mode of logical inference and a 'valid' form of the logic of justification	Probable mode of logical inference and a invalid form of the logic of justification	Possible mode of logical inference and a form of the logic of discovery	Not a mode of logical inference and a form of economic psychology
NEOCLASSICAL ECONOMICS		POST-CLASSICAL ECONOMICS		

5.0 Creative Ecosystem Management

We can finish with another critical ecological insight; given that nature is itself creative, it immediately becomes into reckoning that we as a society need not simply co-evolve with ecosystems, but we maybe able to transform the ecosystem and create entirely novel system states (Folke *et al*., 2002; Walker *et al*., 2004). That is, whilst ignorance and chaotic uncertainty lead the resource manager to discover (*ADEM*) and explore

(*CAEM*) ecosystems, it is the presence of genuine uncertainty that provides the possibilities to create (Dunn, 2000; 2001). Genuine uncertainty, while leading some economists to beliefs of analytical nihilism, allow also for a new degree of optimism and vigour in economic evaluations in that it allows for creativity. Thus, should be asking; "what kind of ecological garden do we as a society want?" And, "what kind of ecological garden can we as a society get?" It is this process of creative ecological engineering, that we coin 'creative ecosystem management' (*CREM*) (see Table 3).

Table 3: Various approaches to ecosystem management.

Approach	*Ontology*	*Uncertainty*	*Causality*	*Analysis*
ANEM	Closed system	Risk	Predictive	Equilibrium
ADEM	Closed system	Ambiguity & ignorance	Towards predictive	Dis-equilibrium
CAEM	Closed system	Chaotic uncertainty	Regularity	Far-from equilibrium
CREM	Open system	Genuine uncertainty	Universal	Non-equilibrium

If we accept the transformability of nature, and consequently the approach of *CREM*, we can now speak of another form of complexity where a complex adaptive system not only interacts with its environment, but also through the creative imaginings of the resource manager of possible systems states (*i.e*. fourth order complexity) (Foster, 2004). Therefore, there is both feedback from nature to the resource manager and feed forward to nature form the creative imagination of the resource manager.

This approach towards ecosystem management of *CREM*, is in direct disagreement with those that favour the conception of naturalness and natural capital, where it is considered that there are no substitutes whatsoever other than that which is occurred, and evolved naturally by the creative processes of the complex adaptive system itself. Indeed, the implication of this is that we must always maintain the stock of natural capital, regardless of the opportunity costs of doing so (Van Kooten & Bulte, 1999). But, in restoration ecology investigations the restoration of ecosystem functioning is often best achieved through the addition of non-native species (Aronson *et al*., 1993; Lockwood & Pimm, 2001). The implications of this finding would seem to be that there is no scientific basis for 'natural' ecosystems to be considered better than created ecosystems.

But, this arcadian thinking of naturalness results in one adhering to the 'naturalistic fallacy'; the unjustified assumption that what exists in nature must inherently be good in itself (Moore, 1908). But, presuming this naturalness belief enshrines a dichotomy between society and nature, a metaphysical separation between the 'vices' of humans from the 'virtues' of nature, which is simply incorrect. After all, since Darwin (1859; 1871) we know we are a 'part of' and not 'apart from' nature, and we already know that we co-evolve with nature, so why not co-create!

6.0 Selected References

Adger, W. N. and Vincent, K., 2005. Uncertainty in adaptive capacity. *C. R. Geoscience*, 337: 399-410.

Arthur, W. B., 1994. Inductive reasoning and bounded rationality. *American Economic Review*, 84: 406-411.

Conlisk, J., 1996. Why Bounded Rationality? *Journal of Economic Literature*, 34: 669-700.

Davidson, P., 1991. Is probability theory relevant for uncertainty? A post Keynesian perspective. *Journal of Economic Perspectives*. 5: 129-143.

Davidson, P., 1996. Reality and economic theory. *Journal of Post Keynesian Economics*, 18: 479-508.

Dequech, D., 2001. Bounded rationality, institutions and uncertainty. *Journal of Economic Issues*, 35: 911-929.

Fankhauser, S., Smith, J. B. and Tol, R. S. J., 1999. Weathering climate change: Some simple rules to guide adaptation decisions. *Ecological Economics*, 30: 67-78.

Folke, C., Colding, J. and Berkes, F., 2002. Synthesis: Building resilience and adaptive capacity in social-ecological systems. *In* Folke, C. (*ed*.). *Navigating Social-Ecological Systems: Building Resilience for Complexity and Change*. Cambridge University Press: Cambridge.

Foster, J., 2004. From simplistic to complex systems in economics. Discussion paper 335, School of Economics, University of Queensland.

Hodgson, G. M., 2002. Darwinisn in economics: From analogy to ontology. *Journal of Evolutionary Economics*, 12: 259-281.

Holling, C. S. and Meffe, G. K., 1996. Command and control and the pathology of natural resource management. *Conservation Biology*, 10: 328-337.

Kauffman, S., 2000. *Investigations*. Oxford University Press: New York.

Lawson, T., 1997. *Economics and Reality*. Routledge: London.

Loasby, B., 1999. *Knowledge, Institutions and Evolution in Economics*. Routledge: London.

Potts, J., 2000*a*. *The New Evolutionary Microeconomics*. *Edward Elgar*: Cheltenham.

Potts, J., 2000*b*. Uncertainty, complexity and imagination. *In*, Earl., P. E. and Frowen, S. (*eds*.). *Economics as an Art of Thought*. Routledge: London.

Reichertz, J., 2004. Abduction, deduction and induction in qualitative research. *In* Flick, U., von Kardorff, E., and Steinke, I. (*eds*.). *A Companion to Qualitative Research*. Sage: London.

Rosser, J. B., 1999. On the complexities of complex economic dynamics. *Journal of Economic Perspectives*, 13: 169-192.

Runde, J., 1998. Assessing causal economic explanations. *Oxford Economic Papers*, 50: 151-172.

Shackle, G. L. S., 1955. *Uncertainty in Economics and Other Reflections*. Cambridge University Press: Cambridge.

Simon, H. A., 1959. Theories of decision-making in economics and behavioural science. *American Economic Review*, 49: 253-283.

Tversky, A. and Kahneman, D., 1974. Judgment under Uncertainty: Heuristic and Biases. *Science*, 185: 1124-1131.

Walker, B., Holling, C. S., Carpenter, S. R. and Kinzig, A., 2004. Resilience, adaptability and Transformability in Social-ecological systems. *Ecology and Society*, 9: 5-13.